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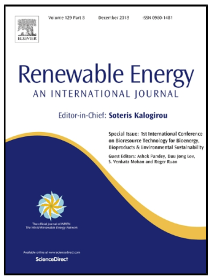

A multi-objective optimization methodology for window design considering energy consumption, thermal environment and visual performance

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The Title: A multi-objective optimization methodology for window design considering energy consumption, thermal environment and visual performance

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A multi-objective optimization methodology for window design considering energy consumption, thermal environment, and visual performance

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Abstract

Window design involves various parameters such as the orientation, window size, and glass material. These parameters have a significant, interactive influence on the building performance. Therefore, it is important to simultaneously optimize the window parameters to determine trade-off design solutions between energy consumption, indoor thermal environment and visual performance. In this paper, a multi-objective optimization method that combines the Non-dominated-and-crowding Sorting Genetic Algorithm II (NSGA-II) with EnergyPlus is proposed for window design optimization. The method takes many parameters into consideration and optimizes several objectives to assess their overall performance. It is applied to an office room with various window parameters and three building design objectives. The Pareto approach is used to select optimal solutions. All Pareto-optimal solutions are shown in the Pareto-frontier charts, which clearly illustrate the performance of each solution. A preliminary analysis of Pareto-optimal solutions was performed to illustrate the value distribution of the window parameters for each orientation. The method provides the architects rich and valuable information about the effects of the parameters on the different building design objectives. It can help the designers to obtain an optimal window design solution to minimize the building energy consumption while simultaneously improving the indoor thermal environment and visual performance.

Keywords: Multi-objective optimization; window design; NSGA-II; energy consumption; thermal environment; visual performance

1. Introduction

In the early stage of building design, designers should consider many design possibilities and have to make the majority of decisions in the entire process [1-3]. Choosing the appropriate window area and material is part of early design stage decisions, which are hard to change later.

It is well-known that windows have a considerable effect on building performances such as energy

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consumption, indoor thermal environment, and visual comfort. The effects of window parameters on the building performance mostly interact with each other. For example, large windows will allow more daylight in the room and improve the indoor visual comfort, but they might also result in excessive heat gains or losses, which affect the indoor thermal environment and energy consumption.

On the other hand, window design involves multiple parameters such as the window–wall ratio (WWR), glazing, and filling gas of the window material. Changing one parameter while leaving others constant could potentially lead to the failure to notice important interactive effects.

Window design is therefore typically a multi-factor and multi-objective optimization problem. It is important to simultaneously optimize the window parameters in the early stage of building design and find a balance between the energy consumption, indoor thermal environment and visual performance.

Single objective optimization of the window system is frequently described in literature. Most of the studies focus on the energy performance for heating, cooling, and lighting in buildings [4, 5]. Susorova et al. [6] evaluated the effect of geometry factors, such as the window orientation, WWR, and room width to depth ratio, on the building energy performance in a commercial office building. Thalfeldt et al. [7] optimized the facade parameters, such as the window type, wall insulation, WWR, and shading devices, for the best energy performance. Su and Zhang [8] focused on the environmental impact of a typical office building to determine a suited limited value for the WWR for different orientations and window materials. Ma et al.[9, 10] studied the relationship in thermally autonomous buildings between maximum WWRs and the ambient temperature amplitudes with different thermal envelope resistances. Lee et al.[11] optimized the annual heating, cooling, and lighting energy consumption in five typical climate zones in Asian regions by analyzing the window properties such as the WWR, U-value, solar heat gain coefficient (SHGC), and visible transmittance. Hiyama and Wen [12] proposed a rapid response surface creation method to optimize the window geometry using dynamic daylighting and energy simulations.

Some focus has been placed on the daylighting performance and potential energy savings. Most studies focus on performance assessment and prediction. The optimization of the daylighting performance and energy savings are implemented separately. Yu et al. [13] presented the metrics and methods for indoor daylight availability assessment and the estimation methods used for predicting potential energy savings from daylight. A method to predict the potential energy savings for lighting using an ideal window area concept is presented by Ghisi [14] for effective daylight integration with an artificial lighting system. Mangkuto et al. [15] investigated the influence of the WWR, wall reflectance, and window orientation on various daylight metrics and the lighting energy demand in simple buildings located in the tropical climate. Krarti et al. [16] proposed a simplified method to estimate the energy savings of artificial lighting by investigating several combinations of building geometries, window opening sizes, and glazing types for four geographical locations. A generalized window energy rating system (WERS) for typical office buildings has been presented by Tian et al.[17] and the energy effects of window parameters have been analyzed and indicated using the localized WERS.

Recently, several studies focused on the window design with simultaneous optimization of the energy and daylighting performance[18]. However, the research is insufficient [19] and the optimization process is very complex without consideration of the interaction of the window parameters. Ochoa et al. [20] used a graphical optimization method to determine the window size when simultaneously optimizing the low-energy consumption and high visual comfort. Vanhoutteghem et al. [21] determined the appropriate window solution by evaluating the effect of the window design parameters on the heating demand, daylighting, and thermal environment using a contour plot.

With the rapid development of computational science and mathematical optimization methods, studies in building engineering that combine a building energy simulation program with an algorithmic optimization engine have been published in the late 2000s [19, 22]. The Genetic Algorithm (GA) is the most popular simulation-based optimization method applied to building design. The Non-dominated-and-crowding Sorting Genetic Algorithm II (NSGA-II), which is a variation of the GA, was developed by Deb [23] for multi-objective optimization. Gagne et al.[24] presented a GA-based tool to optimize the facade design process based on illuminance and glare objectives. Magnier and Haghghat [25] used the GA, TRNSYS, and Artificial Neural Network (ANN) for multi-objective optimization of the building design. Different types of genetic algorithms [26-29] were used for building design problems.

In this paper, a multi-objective optimization method combining EnergyPlus and NSGA-II is presented to obtain optimal window design solutions. The comparison between the reviewed studies and this paper is shown in Table 1. The summary is as follows:

1) Most of the studies focus on single-objective optimization and a large proportion of the optimization objectives in the studies focus on the energy performance. Studies that focus on the daylight and thermal comfort are much fewer than that related to the energy performance.

In this paper, a multi-objective optimization method is proposed, which takes the energy consumption, thermal comfort, and visual performance into consideration simultaneously to obtain a balance between the three objectives. The drawback of single-objective optimization can be avoided, which potentially leads to the failure to notice important interactive effects between different objectives. The multi-objective optimization method of this paper is therefore more practical than single-objective optimization.

2) The optimization method in the reviewed studies can be grouped into five categories: graphical analysis, regression analysis, objective prediction model and analysis, multi-factor combination exploration, and intelligent optimization algorithm. The graphical and regression analyses methods are simple and illustrative; however, there is some subjectivity and less accuracy in the optimization process. The objective prediction model provides the objective value easily and fast. However, the establishment of the prediction model is very complex and there is relative deviation between the actual objective value and the prediction value. Multi-factor combination exploration chooses an optimal solution from a set of specified values for each parameter and therefore only covers the partial design space of the building parameters.

In this paper, the well-known, intelligent optimization algorithm NSGA-II is introduced and combined with EnergyPlus to optimize the three building design objectives simultaneously. The NSGA-II can optimize the parameter values based on global optimization using the evolutionary concept of natural selection. In the optimization process, the three-building performance can be accurately calculated using EnergyPlus. The optimization method is therefore more efficient and effective than other methods. There are few solutions for multi-objective optimization, which are optimal for any objective. M. Di Somma et al.[30, 31] use the Pareto front in the design optimization of distributed energy systems to get the trade-offs between different objectives. The research proved the feasibility of the Pareto approach applied in the building optimization related problems. In this paper, the Pareto approach is introduced into the optimization process and all Pareto-optimal solutions are plotted as Pareto frontier. The Pareto frontier chart provides rich and valuable information about the effects of the value change of the window parameters on the different design objectives. Subsequently, building designers can identify one or more appropriate compromised solutions from the sets of Pareto-optimal solutions. The Pareto approach and the Pareto frontier are proved to be effective in the multi-optimization problem.

Table 1 Comparison between reviewed literature and this paper

Author	Performance metrics	Design parameters	Optimization method	Character
Li (2018) [1]	Energy consumption	Building form and facade	Energy prediction model and analysis	Single-objective optimization
Zhou (2018) [4], Su (2010) [8]	Environmental performance	WWR, orientation, window materials	Multi-factor combination exploration	Single-objective optimization
Kwon (2018) [5]	Energy Saving	Slat angle in blinds, orientation, WWR	Multi-factor combination exploration	Single-objective optimization
Bamdad (2017) [32]	Energy Saving	Building envelop and orientation	Ant colony optimization + EnergyPlus	Single-objective optimization
Tuhus-Dubrow (2010) [26]	Energy consumption	Building shape and envelope	GA + DOE-2	Single-objective optimization
Lee (2013) [11]	Energy consumption	Window types and properties	Graphical analysis+ Regression analysis	Single-objective optimization
Susorova (2013) [6]	Energy performance	Building shape, window orientation, WWR	Multi-factor combination exploration + Design Builder	Single-objective optimization
Ferdyn-Grygierek (2017) [28]	Life cycle costs	Window types, size, building orientation, insulation of external wall, roof and ground floor and infiltration	GA + EnergyPlus	Single-objective optimization
Baglivo (2017) [33]	Indoor thermal comfort	Building envelope	Multi-factor combination exploration + TRNSYS	Single-objective optimization
Krarti (2005) [16]	Energy savings of artificial lighting use from daylighting	Building geometry, window opening size, and glazing type	Regression analysis + Illuminance calculation model	Single-objective optimization
Gagne (2012) [24]	Daylighting performance	Facade designs	GA+ Lightsolve Viewer (LSV)	Single-objective optimization
Méndez Echenagucia (2015) [2]	Energy need for heating, cooling and lighting	Number, position, shape, and type of windows and thickness of the masonry walls	NSGA-II + EnergyPlus	Three closely related objective about energy performance
Ochoa (2012) [20]	Energy consumption and visual performance	Window sizing	Graphical analysis + EnergyPlus	Two-objective optimization
Lin (2018) [29]	Thermal load and discomfort degree hour	Building envelope	GA + Multiple Linear Regression (MLR) / ANN prediction model	Two-objective optimization
Magnier (2010) [25]	Thermal comfort and energy consumption	HVAC system settings, thermostat programming, and passive solar design	ANN prediction model + GA + TRNSYS	Two-objective optimization
Mangkuto (2016) [15]	Daylight performance and lighting energy demand	WWR, wall reflectance, and window orientation	Sensitivity analysis + Graphical analysis	Two-objective optimization
Zhang (2017) [18]	Energy use, summer discomfort, Daylight illuminance	Building orientation, building shape, WWR, glazing material, and shading types	EnergyPlus + Radiance + Octopus	Three-objective optimization
Lee (2016) [34]	Energy performance, environmental impact, and cost effectiveness	Insulation values, construction types, skylight coverage, and transpired solar collector coverage	Graphical analysis + design support approach	Three-objective optimization
Vanhoutteghem (2015) [21]	Heating demand, daylighting and thermal	Window size, orientation, and glazing properties of	Graphical analysis	Three-objective optimization

	environment	facade windows		
This paper	**Energy consumption, indoor thermal environment and visual performance**	**WWR, orientation and glazing material**	**NSGA-II + EnergyPlus**	Three-objective optimization

The methodology of the multi-objective optimization method is described in Section 2. It is then applied to a case study to illustrate its implementation in Section 3. The results and discussion of the optimization are shown in Section 4. Finally, conclusions are drawn in Section 5.

2. Methodology

2.1 Structure of the multi-objective optimization method

This paper presents a multi-objective optimization method based on NSGA-II combined with EnergyPlus to optimize the value setting of the window parameters. The structure of the method is shown in

Fig. 1. It is applied to a case study in Section 3.

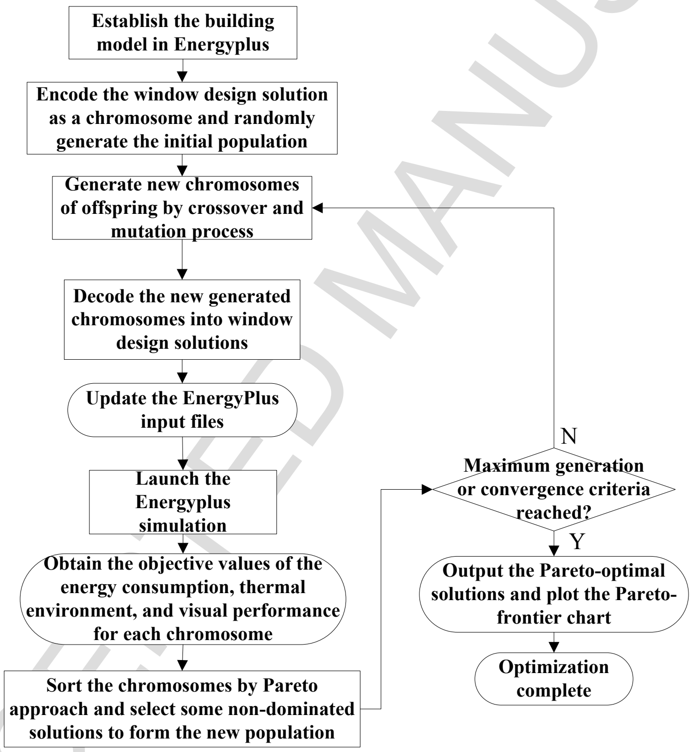

Fig. 1 Flowchart for the multi-objective optimization method

In

Fig. 1, the building for which the window parameters are to be optimized is modeled with EnergyPlus. The NSGA-II, which is written in Matlab is used as optimization algorithm. In the optimization process, the window design solution is encoded as chromosome. The initial population, which corresponds to a set of window design solutions, is randomly generated to undergo the crossover and mutation process. For each window design solution, the objective values for the energy consumption, thermal environment, and visual performance are obtained from simulations in EnergyPlus and are saved as .csv files that can be read by Matlab. In the optimization process of NSGA-II, the new generated chromosomes are decoded into the window design solutions. Based on the window design solutions, the EnergyPlus input files are updated by Matlab and implemented for the simulation of the energy consumption, thermal environment, and visual performance. After the Energyplus simulation, Matlab gets the objetive values from the .csv files and continue the following optimization. The Pareto approach and tournament selection method are used to select Pareto-optimal window design solutions for the designer to make the final design decision.

2.2 NSGA-II

The NSGA-II is based on the evolution of a population of “individuals.” Each individual corresponds to a solution of an optimization problem. In this paper, an individual represents a window design solution. To use a genetic analogy, each individual is represented by a chromosome with genes corresponding to the values of the window parameters, as shown in

Fig. 2.

The first generation of the population is randomly selected. The population then undergoes the crossover and mutation process to generate offspring. All chromosomes of the individuals are decoded to update the corresponding EnergyPlus input files and the simulations are subsequently launched to obtain the optimization objective values. The Pareto approach is applied to sort the individuals based on their objective values and some optimal individuals are selected to form the next generation. The mating of the next generation will then begin. The procedure described above iterates until convergence criteria are reached. The convergence criterion is the moment when there are few new generated optimal individuals for a few generations or the maximum generation is reached.

The Pareto approach and the selection of the Pareto-optimal solution are described in the next section.

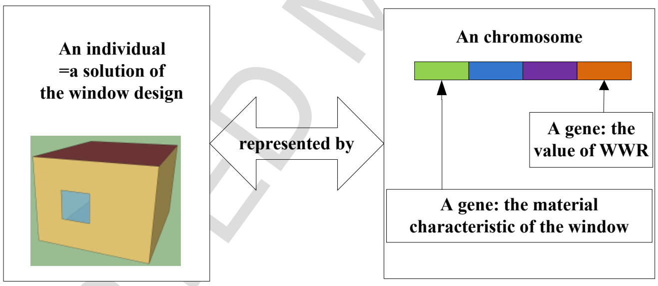

Fig. 2 A solution to an optimization problem, as represented by a chromosome

2.3 Pareto approach

Multi-objective optimization differs from single-objective optimization in the fact that, in order to compare two solutions and determine which one is best (solutions A and B for example), their performances need to be considered in multiple objectives and not just one. If objective functions are contrasting, it may not be the case that solution A outperforms B in all functions; it may be the case that A outperforms B in one function but B outperforms A in another. This relationship is studied with the concept of dominance by Pareto approach, which can be summed up with the following statements [35]:

- If solution A outperforms solution B in at least one objective and outperforms or equals solution B in all the other objectives, then solution A dominates solution B;
- If solution A outperforms solution B in one or more objectives and at the same time solution B outperforms solution A in one or more objectives, then solution A and B do not dominate each other.

The Pareto approach is applied in multi-objective optimization to treat the optimization objectives individually, and arrives at compromises between them by identifying solutions that are non-dominated or "Pareto-optimal."

2.4 Selection of the Pareto-optimal solution

In the optimization process of the multi-objective optimization method, all individuals are sorted by the Pareto approach to form the next generation. Individuals that are not dominated by any other are assigned to front number 1. Individuals dominated only by individuals in front number 1 are assigned to front number 2, etc and so on. Each individual in each front is assigned a rank value based on the front to which it belongs. Meanwhile, each individual is assigned a ''crowding distance," which is a measure of how close an individual is to its neighbors. A large average crowding distance indicates a high degree of diversity.

The individuals with low rank number and high crowding distances are selected using binary tournament selection to form the next generation.

2.5 Pareto frontier

At the end of the optimization process, a set of Pareto-optimal (non-dominated) solutions were obtained and plotted as Pareto frontier. Fig. 3 shows an example of a Pareto frontier for an optimization problem with two objectives for minimization. Based on the Pareto frontier chart, the performance of the Pareto-optimal solution can be seen clearly.

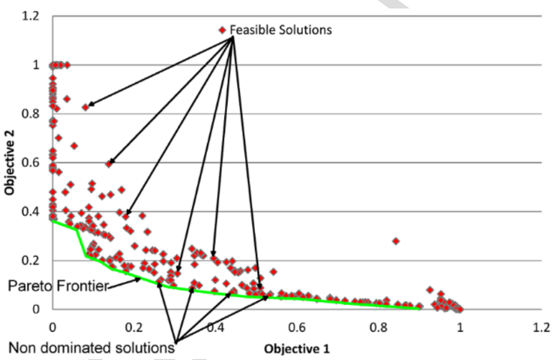

Fig. 3 Example of a Pareto frontier [22]

3. Application to a case study

In this section, the multi-objective optimization method was applied to the window design optimization of a test room.

3.1 Description of the test room

The multi-objective optimization method began with a hypothetical office room (dimensions 5.0 × 4.0 × 3.0 m) with a single external wall (Fig. 4). The external wall accommodates a single window opening in its center.

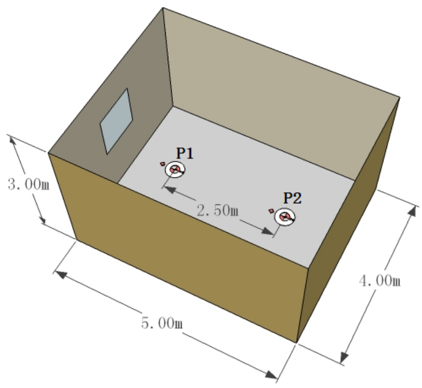

Fig. 4 The geometry of the test room

The test room was modeled using EnergyPlus as whole-building simulation software [20]. The U-value of the external wall was set to comply with the Buildings Design Standard of China (0.43 W/m^{2}K: 100 mm brick, 200 mm heavyweight concrete, 50 mm insulation board, and 19 mm gypsum board). The rest of the components were assumed to be adiabatic because the use of lightweight partitions has become the most widespread solution for commercial buildings and provides a way to express the building energy usage per square meter. The ''Ideal Loads Air System'' of EnergyPlus was used. The lighting load, people density, and electric equipment load were set to 9 W/m^2, 10 m^2/person, and 15 W/m^2, respectively. The occupancy, lighting, and electric equipment schedules were set as shown in Fig. 5 based on the regular work schedule in China. Heating and cooling set point temperatures were respectively set to 20 °C and 26 °C from 7.00 AM to 9.00 PM during weekdays only.

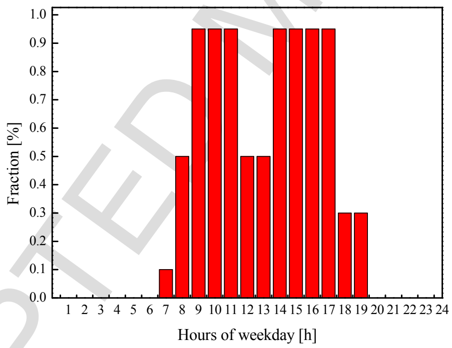

Fig. 5 Occupancy, lighting, and electric equipment schedules

The window was double-pane glazed without any shading device. Electric lighting was controlled through a two-zoned automatic dimmer, supplementing natural light at the working plane (0.8 m from the floor). The illuminance was measured at two control points (P1 and P2 in Fig. 4), which correspond to the center of each lighting zone.

To calculate the energy consumption of the test room, the weather data should be set in advance in EnergyPlus. In this paper, the climate of Xi'an in China (34°16′ N, 108°54′ E) was used for the simulation. It is characterized by hot summers and cold winters. There are approximately 1646–2114 sunshine hours per year. The average winter temperatures range between -1.2 °C and 0 °C, with a minimum temperature of -21.2 °C. During summer, this range is 26.3 °C–26.6 °C and a maximum temperature of 43.4 °C has been recorded. The weather data used in the simulation process were downloaded from the Chinese Standard Weather Data and the simulation process was performed using EnergyPlus (version 8.1).

3.2 Optimization process

The multi-optimization method in this paper combines the NSGA-II with EnergyPlus to optimize the window parameter settings. The optimization process was performed according to the flowchart in

Fig. 1. The options of the EnergyPlus model for the test room were set according to Section 3.1. In NSGA-II, the GA parameters were set as shown in Table 2. When the iteration of the evolutionary process reaches the maximum generation, the optimization stopped and the final optimal solutions were output.

Table 2 General preferences of the NSGA-II

Population size	Crossover rate	Mutation rate	Maximum generation
20	1.0	0.2	200

3.2.1 NSGA-II input (parameter variations)

To focus on the multi-optimization method rather than on the details of the specific performance of each window parameter, we selected some window parameters to be optimized for illustration. The variations of the parameters are shown in Table 4.

In the beginning of NSGA-II, the value of each window parameter was randomly selected from Table 3. Each window parameter was then encoded as a gene. All genes were combined to form a chromosome. In the crossover and mutation process, the value of each gene should be limited to the variations shown in Table 4.

Table 4 Variations of the window parameters

Window parameters	Variations
WWR	0.1/0.2/0.3/0.4/0.5/0.6/0.7/0.8/0.9
Orientations	North/South/West/East (N/S/W/E)
Outer glass of the double-paned window	Clear3mm, Clear6mm, Clear12mm, LoEClear3mm, LoEClear6mm, Bronze6mm, Grey6mm, Green6mm, LowIron5mm, Blue6mm, Coatedpoly-44
Filling gas of the double-paned window	Air3mm, Air6mm, Air8mm, Air13mm, Argon3mm, Argon6mm, Argon8mm, Argon13mm
Inner glass of the double-paned window	Clear3mm, Clear6mm, Clear12mm, Bronze6mm, Grey6mm, Green6mm, LowIron5mm, Blue6mm

Note: The variations of outer and inner glass are from the file "WindowGlassMaterials.idf" in the EnergyPlus which provides detailed glass material properties. The variations of filling gas are from the file "WindowGasMaterials.idf" in the EnergyPlus which provides detailed gas material properties. The number with "mm" subsequently in the variation's name means the thickness of each material. For example, Clear3mm is the glass with a thickness of 3 mm.

Clear3MM, Clear6MM and Clear12MM are the glasses with no impurities added to glass mix; LowEClear3MM, LoEClear6MM are the glasses with low-emissivity metallic coating; Bronze6mm, Grey6mm, Green6mm, LowIron5mm, Blue6mm are the glasses tinted the indicated color; Coatedpoly-44 is the glass coated polyester film with nominal visible transmittance of 40 percent.

3.2.2 Optimization objectives

For the multi-objective optimization method in this paper, the energy consumption, indoor thermal environment and visual performance were the optimization objectives (Table 5). The specific values of the objectives during the optimization process were obtained by the simulations of EnergyPlus. All optimization objectives should be minimized to obtain a better window design solution.

Table 5 Optimization objectives of the multi-objective optimization method

Evaluation criteria	Optimization objective	Unit	Representing character
Energy consumption	Total annual energy consumption of heating, cooling, and lighting	kWh/(m^2·a)	f_1
Indoor thermal environment performance	Hours when the thermal performance is not in the ASHRAE 55-2004 summer or winter clothes region	hr	f_2
Indoor visual performance	The ratio of hours of the daylight illuminance at P2 below 500 lux	%	f_3

The objective of energy consumption is the annual total thermal load including heating, cooling, and lighting energy consumption. The objective of indoor thermal environment performance is the total number of discomfort degree hours. For the evaluation of the visual performance in the test room, the illuminance at control point P2 in Fig. 4 was chosen as quantitative indicator because P2 has worse daylight performance than P1. Normal office tasks were assumed to be performed with an illuminance target level of 500 lux, as stated in NEN-EN 12464-1: 2011 such that the ratio of hours of daylight illuminance at P2 below 500 lux was calculated as the optimization objective for visual performance evaluation.

The objective functions are described as follows:

$$\begin{aligned} &\min f_1 = Q_C + Q_H + Q_L \\ &\min f_2 = \sum_{i=1}^{8760} t_i \\ &\min f_3 = \sum_{i=1}^{8760} v_i / 8760 \end{aligned} \tag{1}$$

$$\text{subject to:} \quad ti = \{0,1\}, \quad vi = \{0,1\}$$

where Q_C, Q_H, and Q_L are the energy consumptions for heating, cooling, and lighting, respectively; $t_i = 1$ when the thermal performance is not in the ASHRAE 55-2004 summer or winter clothes region at time i; otherwise, $t_i = 0$; and $v_i = 1$ when the daylight illuminance at P2 is below 500 lux at time i; otherwise, $v_i = 0$.

Because the multi-optimization method uses NSGA-II to optimize the window parameter settings, the value constraints of each window parameter are integrated in the optimization process. Therefore, the value variation of each gene in the entire optimization process should be limited to the variations in Table 4.

4. Results and discussion

The optimization results for the window parameters for the test room are shown in Fig. 6. For each orientation, the multi-optimization method generated more than 700 design solutions, which are displayed in two-dimension diagrams (f_1 and f_2, f_1, and f_3, f_2 and f_3). Each point in Fig. 6 represents a window design solution and the red points are the Pareto-optimal solutions that cannot be improved in one optimization objective without worsening another.

All Pareto-optimal solutions form the Pareto frontiers, which can be discerned clearly.

For each orientation in Fig. 6, there are a number of optimal solutions, which provide the window designer rich and valuable information about the solution performances. The window designers can choose one or more window design solutions in the Pareto frontiers according to their desired performance. The number of Pareto-optimal solutions for each orientation is shown in Table 6. According to literature [20], there is little research on minimal acceptance criteria using time-based performance metrics. Therefore, we assume a 50% visual performance satisfaction time during occupancy for the test room. The number of Pareto-optimal solutions with an illuminance at P2 ≥500 lux for 50% occupancy hours is shown in Table 6.

Table 6 Number of Pareto-optimal solutions for the window design

Orientation	Number of Pareto-optimal solutions	Number of Pareto-optimal solutions with an illuminance at P2 ≥ 500 lux for 50% occupancy hours
North	72	49
South	210	62
East	76	33
West	166	123

4.1 Detailed analyses of the optimization results

The Pareto frontiers of f_1 and f_3 in Fig. 6 show that the hours of daylight illuminance at P2 below 500 lux (objective f_3) decrease for the four orientations when the total annual energy consumption (objective f_1) increases. That is, if the indoor visual performance improves, the energy consumption will increase. That is because the better the indoor visual performance is, the bigger is the WWR. However, the thermal insulation properties of windows are worse than that of the wall. Therefore, the energy consumption will increase. Thus, the energy performance varies inversely with the visual performance as the window parameters vary.

The Pareto frontiers of f_2 and f_3 show that the hours of daylight illuminance at P2 below 500 lux (objective f_3) decrease when the hours of the discomfortable thermal environment (objective f_2) increase. This means that the thermal environment performance varies inversely with the visual performance. The reason for that may be that the increase of the WWR gives rise to more indoor daylight. However, more energy is needed to maintain the thermal comfort. Thus, when the energy consumption remains the same, the indoor visual performance increases with increasing WWR, whereas the indoor thermal comfort decreases.

There is no clear relationship between the total annual energy consumption (objective f_1) and the hours of the discomfortable thermal environment (objective f_2). The reason for that may be that the indoor thermal comfort is not only related to the energy consumption but also to the heat gains from solar radiation and other factors.

From Fig. 6, the variation range of the energy consumption of the South orientation is narrow, and the energy consumption is below 90 kWh/m^2·a for 96.8% of the Pareto-optimal solutions, since the room in the South get more heating gain from solar radiance in winter.

The maximum energy consumption of the North orientation in the Pareto-optimal solution set is about 95 kWh/m^2·a. However, it increases to almost 220 kWh/m^2·a for the West orientation because the room at West gets too much heating from the solar radiance in summer, which results in the increase of the cooling energy consumption. Thus, more attention should be paid to the West-oriented room with respect to window design energy savings.

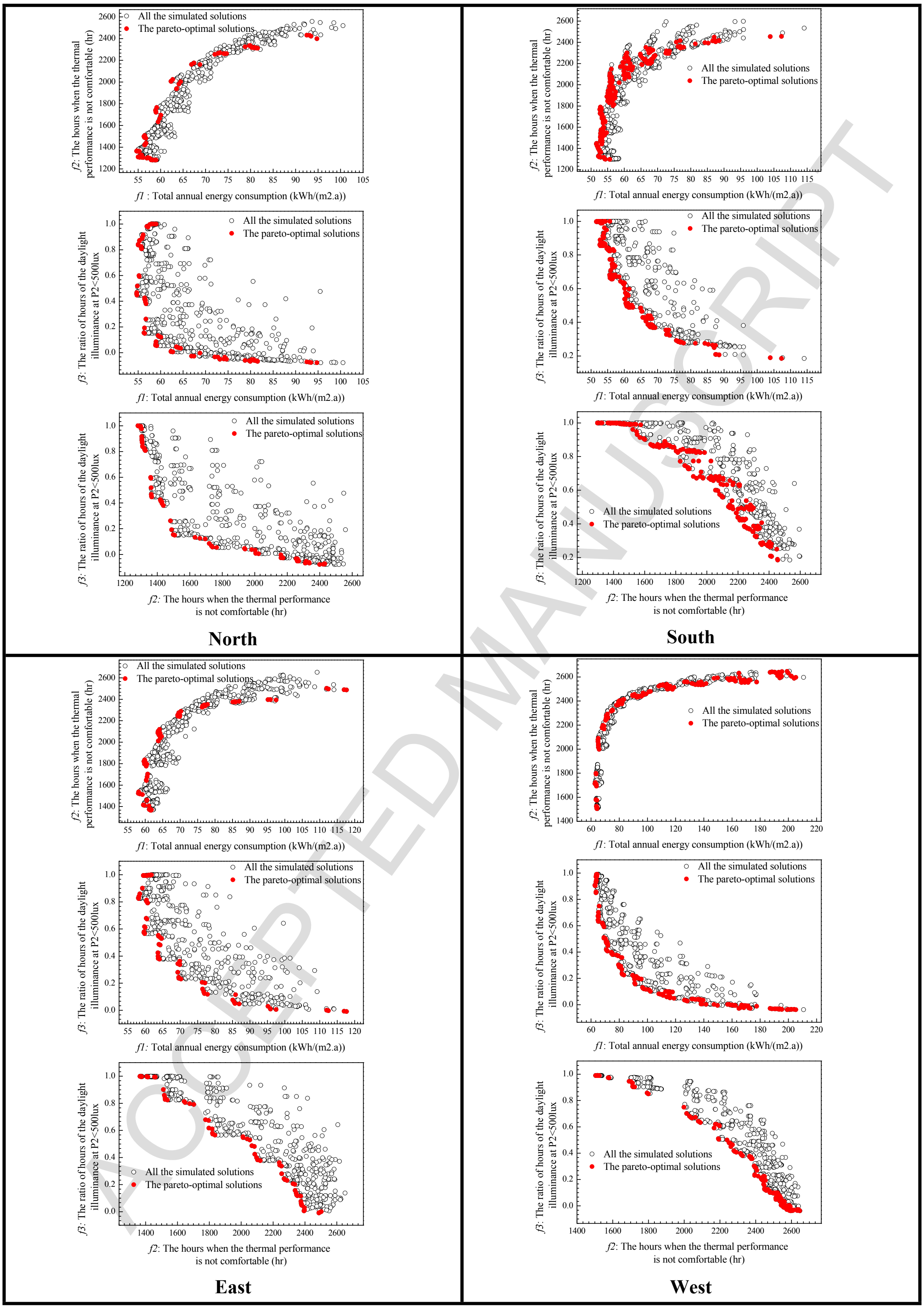

Fig. 6 Results of the multi-objective optimization of the energy consumption, thermal environment, and visual performance (f_1, f_2, and f_3)

4.2 Value distribution of the window parameters in the Pareto-optimal solution set

Fig. 7 shows the value distribution of the window parameters in the Pareto-optimal solution set for the N/S/W/E orientations. The vertical axis is the frequency of each variation of the window parameter in the Pareto-optimal solution set. Fig. 7 provides the window designer suitable values for each parameter. The details are as follows:

As shown in Fig. 7, to minimize the multi-objectives in Table 5, the minimum WWRs for each orientation are North = 0.3, South = 0.6, East = 0.5, and West = 0.4.

For whether outer or inner glass, the glasses Bronze6mm, Grey6mm and Blue6MM are not in the Pareto-optimal solution set. Therefore, it would be unwise to select the three glass materials for the window design.

For the selection of the outer glass material of the double-paned window, LoEClear3MM and LoEClear6MM are recommended for the North and East orientations. The glass materials LoEClear3MM, LoEClear6MM, and Green6mm are recommended for the South orientation. The materials Clear3mm, Clear6mm, LoEClear6MM, and Green6mm are recommended for the West orientation.

For the selection of the inner glass material for the double-paned window, no matter which orientation, LowIron5mm is the first choice; Clear3mm is the second choice.

The optimal materials for the filling gas of the double-paned window are Argon13MM (North); Air3MM, Air6MM, and Argon3MM (South); Argon13MM (East); Argon13MM, Air13MM, and Argon8MM (West).

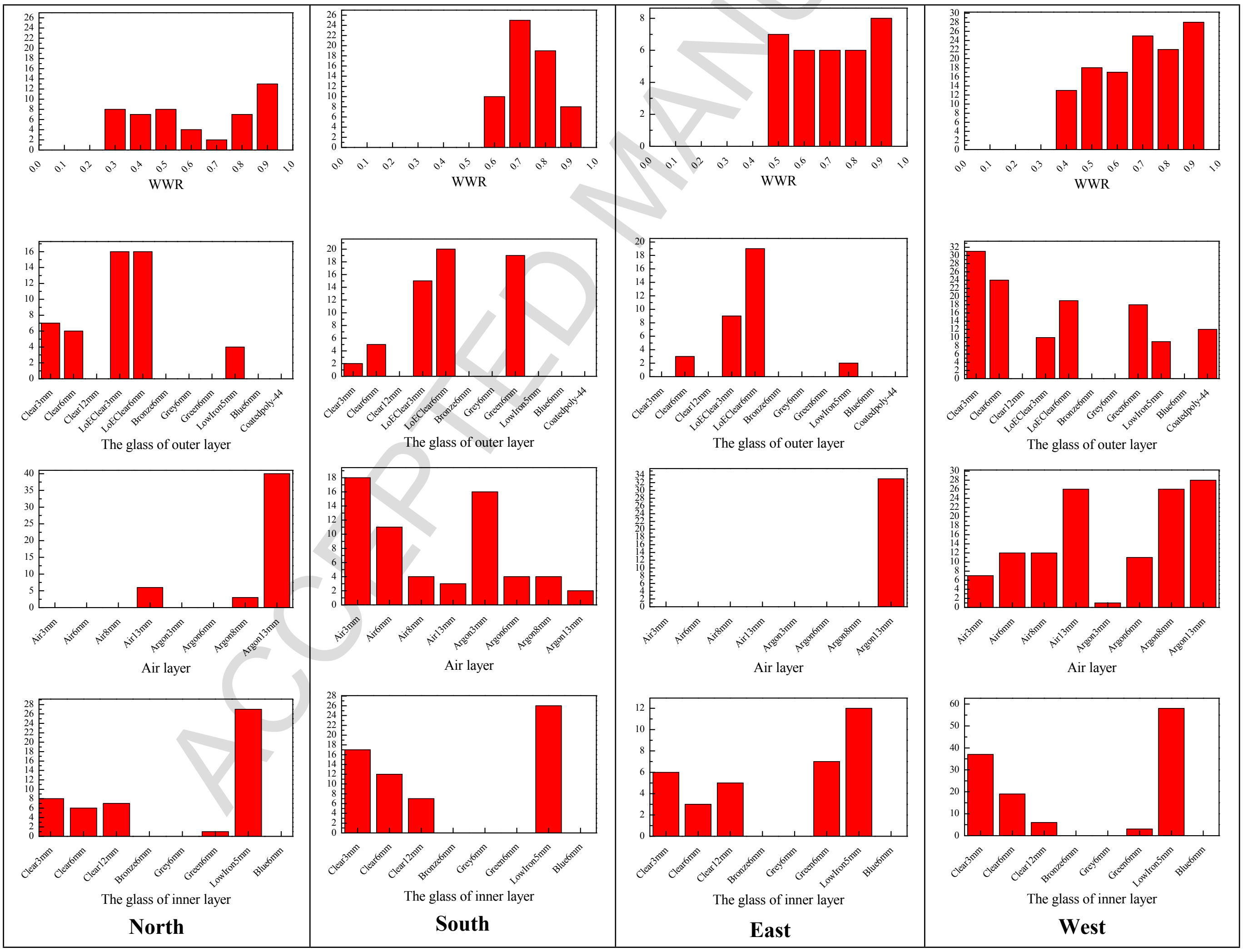

Fig. 7 The value distribution of the window parameters in the Pareto-optimal solution set at N/S/W/E

4.3 Further discussion of the multi-objective optimization method

To further illustrate the multi-objective optimization method, Table 7 highlights several design solutions of the optimization results of the North orientation. In Table 7, Design solutions 1－4 are the Pareto-optimal solutions and design solution 5 is not a Pareto-optimal solution. The comparisons of the solutions are as follows:

For design solution 1, the total annual energy consumption is the lowest, while the indoor visual performance is unsatisfied. For design solution 2, the WWR is the smallest; thus, the indoor visual performance is the worst, while the thermal environment performance is the best. On the contrary, for Design solution 3, the WWR is the biggest; accordingly, the indoor visual performance is the best. However, the thermal environment performance is worse.

The solution performances of design solutions 1－3 are in accordance with the analysis in Section 4.1, that is, the energy performance varies inversely with the visual performance as the window parameters vary and the thermal environment performance also varies inversely with the visual performance.

For design solution 4, all three optimization objectives are neither better nor worse. For the design solution 5, which is not the Pareto-optimal solution, although the WWR is the biggest, the indoor visual performance is poor. Also, the energy consumption and thermal performance are both worse. Thus, it is essential to use the Pareto approach for multi-objective optimization to find the Pareto-optimal solutions.

In addition to the solutions in Table 7, there are many design solutions in Fig. 6. Based on Fig. 6, the designers are in full control of what they want (desired performance). It can be observed that there are many alternative design solutions for similar energy consumption performances that yield positive thermal or visual performances. Therefore, the multi-objective optimization method provides more optional solutions for the designers. How to choose the final design solution depends on the style and preference of the designers. For example in Table 7,, if the window designers focus on the energy consumption, then design solution 1 is the first choice (Table 7). If the window designers focus on the thermal performance, then design solution 2 is the first choice. If the window designers focus on the visual performance, then design solution 3 is the first choice. Furthermore, the window designers can also choose other design solutions from the Pareto-optimal solution set.

Table 7 Design solution examples and their optimization performances

Parameters	**Design solution 1**	**Design solution 2**	**Design solution 3**	**Design solution 4**	**Design solution 5**
WWR	0.4	0.1	0.9	0.5	0.9
Outer glass of the double-paned window	LoEClear6MM	LoEClear6MM	LowIron5MM	LoEClear6MM	Bronze6MM
Filling gas of the double-paned window	Argon13MM	Argon13MM	Argon13MM	Argon13MM	Air3MM
Inner glass of the double-paned window	LowIron5MM	Grey6MM	LowIron5MM	Clear12MM	Grey6MM
Optimization objectives					
Total annual energy consumption of heating, cooling, and lighting (kWh/m2·a)	54	59	94	56	95

Hours when the thermal performance is not in the ASHRAE 55-2004 summer or winter clothes region (hr)	1364	1281	2339	1488	2547
Ratio of hours of the daylight illuminance at P2 below 500 lux	0.46	1.00	0.00	0.19	0.47

5. Conclusion

In this paper, a multi-objective optimization method based on NSGA-II in combination with EnergyPlus is proposed to optimize the window parameter settings and obtain a balance between energy consumption, thermal environment, and visual performance. This method can simultaneously consider multi-parameters and optimize several objectives to assess their overall performance. It can avoid one-sidedness and conflict due to the optimization of exclusively one objective. Thus it is more practical than the conventional single-objective optimization for considering the important interactive effects between different objectives. Compared with the other optimization method, the proposed method optimizes the parameter values based on global optimization using the evolutionary concept of natural selection. In the optimization process, the Pareto approach is used to select the optimal window design solutions. And the Pareto frontier chart which contains all solutions can clearly illustrates the performance of each solution. Therefore the designers can be in full control of what they want (desired performance). In addition, the method can provide many alternative solutions for the designers to choose. Thereby it is comprehensible and helpful for the window designer.

The results of the case study demonstrate that the objective of energy consumption varies inversely with the visual performance as the window parameters vary and the indoor thermal environment performance varies inversely with the visual performance. The discuss on the Pareto frontiers shows that the variation range of the energy consumption of the South-oriented room is narrow, and the maximum energy consumption of the West-oriented room is more than two times higher than that of the North-oriented room. In addition, whether outer glass or inner glass, it would be unwise to select the glasses Bronze6MM, Grey6MM, and Blue6MM as glass material for the double-paned window.

The proposed method can be applied in the practical window design problem. Given the parameter variations and the optimization objectives, it can provide the best trade-off solutions for the building designers. Further research will be carried out to optimize the opaque building envelope and HVAC system. Also, other types of buildings, building costs, and environment aspects should be studied in the future.

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- A multi-objective optimization method is proposed for the window design to minimize the energy consumption while improving thermal environment and visual performance.
- The Pareto approach is used to select the Pareto-optimal window design solutions.
- All Pareto-optimal solutions are shown in the Pareto-frontier charts which provide the architects rich and valuable information about the effects of the parameters on the different building design objectives.